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13. ABSTRACT *(Maximum 200 words)*
Our original research on the multicovariance matched filter deals with optimum low resolution target detection in a single-frame, multicolor image, such as a multispectral infrared or polarimetric synthetic aperture radar picture. The multicovariance method completely uses all the joint variability of the problem, in both space and frequency, in a way that generalizes both the traditional spatial matched filter and also techniques involving scalar ratios between frequency bands. The main new focus of our work, directed toward achieving the best target detection performance that is possible, is to develop a preprocessing step involving optimal adaptive estimation of the local clutter background. This involves segmenting the image into regions, which correspond to different background/clutter statistical models. Statistics of real data are being studied and used in new, state-of-the-art hierarchical segmentation algorithms based on Markov Random Field, polynomial and autoregressive models for vector-valued random processes. The major algorithmic challenges here are in estimating the best possible background/clutter models and in accurately estimating the boundaries between different model regions. We are in the process of developing extremely efficient and robust algorithms to estimate these clutter models. These are similar to familiar algorithms from mainstream signal processing, but solve the interpolation problem for Markov Random Fields, which is different than the usual linear prediction problem.

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Multicovariance Methods and New Fast Signal-Processing Algorithms for Detection of Low-Resolution Targets In Severe Ground Clutter

Final Report for Year Two: June 1994 - December 1994

March 20, 1995

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1 Executive Summary

Last summer, it was declared as a long-term ARPA goal to "**revolutionize wide-area imagery analysis**" (Briefing to URI/ATR Community by Jonathan Schonfeld, 3 August 1994). This is also our goal as a long-term research objective, and we have been studying two main research topics that are directed to this goal:

- New, **highly efficient signal processing techniques to estimate image clutter models**: These methods are similar to highly robust, successful algorithms in one-dimensional signal processing applications, such as speech analysis or linear arrays. But the problems for two-dimensional images are better described as non-causal, interpolation-type statistical models, i.e. **Markov Random Fields** (MRF's). For two-dimensional random phenomena, Markov Random Fields are the most general realistic model for representing the information contained in a large number of highly correlated pixels in an image. By contrast, standard one-dimensional signal processing almost universally uses predictive-type models; these one-sided autoregressive models are excellent for applications such as linear predictive speech coding, but can be rather unstable with respect to model order if one forces them to apply to images ([1]). Thus, to find adequate statistical models for image clutter, we cannot just copy famous one-dimensional algorithms like the Levinson recursion for prediction problems; we have had to develop new algebra and analysis for interpolation-type problems, which is genuinely innovative. But our work is very similar in spirit overall to the trends and techniques in modern one-dimensional signal processing such as Schur methods, split Levinson algorithms, etc.

  Advantages of Lattice Filter Approach: MRF Signal Processing

  - **Computational Efficiency**
    * Generally, matrix inversion has $\mathcal{O}(n^3)$ cost, but Levinson-type methods only $\mathcal{O}(n^2)$ (n = size of sample covariance)
    * Schur methods even better, $\mathcal{O}(n \log(n))$; easy **parallel implementation**
    * Particularly advantageous for multichannel sensors, such as polarimetric SAR, multispectral IR, where a great number of highly correlated statistical parameters must be estimated
  - **Robust**: lattice filters for Toeplitz $\mathbf{R}$ matrices are guaranteed stable; explicit properties (Schur-Cohn test)
  - **Well-Conditioned**: the orthogonalization process creates new, statistically independent variables
  - **Adaptive**: Kailath et. al. have developed theory for **nonstationary** lattices through optimization of generalized performance functional
  - **Order-Recursive**: Easy to build higher-order model out of low-order model

- **Model-based, Bayesian approach to urban clutter**: Our group at Brown has a decades-long experience in applying Bayesian techniques to problems in vision and pattern recognition, such as the original paper on maximum likelihood boundary-finding

([2]), hierarchical Bayesian image segmentation ([3]), and more recently, Bayesian object recognition by polynomial invariants ([4]). One general expertise is in **stochastic/geometric model-building**, involving the use of models such as explicit and implicit polynomials in Gaussian or non-Gaussian noise, to characterize objects in applications such as automated inspection for manufacturing, and robotic navigation. We have also studied stochastic processes for representing variable surface and curve shapes, useful for natural object recognition and other machine vision applications. In this proposal, we describe how to extend stochastic/geometric models to the challenges of urban clutter.

Payoff for ARPA Needs and Requirements: The fast, robust, adaptive algorithms in the first part will help achieve the **lowering of sensor data rates** and computational complexity, resulting in more efficient, streamlined and affordable sensors (CLIPPING SERVICE, AFFORDABLE RADAR). By advancing the state-of-the-art in identifying different image regions (via differences in local statistics), these algorithms also offer the promise of faster, more accurate image segmentation. **Advanced image segmentation methods** are absolutely crucial in order to meet many other current ARPA goals, since they benefit the detection of man-madeness, identification of moving and articulated vehicles, and recognition of characteristic groupings of target populations (MONITOR, DRAGNET, MSTAR). There is no way that simple-minded segmenters such as edge detectors could meet these needs, especially for SAR targets which are better characterized as collections of separate point scatterers rather than as solid geometric shapes. The stochastic/geometric modeling and detection in the second part will lower detection false alarm rates because the Automatic Target Detection (ATD) algorithm will have a better, more accurate model for the clutter inside a target-test-region, and thus permit more accurate decision making in testing the hypothesis of target present versus clutter present in a target-test-region.

2 Overall Research Goals

Our original research in this grant, on the multicovariance matched filter dealt with optimum low resolution target detection in a single-frame, multicolor image, such as a multispectral infrared or polarimetric synthetic aperture radar picture. The multicovariance method completely uses all the joint variability of the problem, in both space and frequency, in a way that generalizes both the traditional spatial matched filter and also techniques involving scalar ratios between frequency bands. This full generalization involves possibly very large matrix blocks, which describe statistical correlations in both space and frequency, not just scalar correlation coefficients between two bands at a time. One of our areas of study is to find simple conceptual models which reduce the complexity of this large linear algebra problem, and which provide insight into the effect of basic system parameters, such as the amount of inter-channel correlation. Performance results coming from these analytical models can be formulated as simple closed-form expressions, as well as ROC curves, etc.

A second focus of our work, directed toward achieving the best target detection perfor-

mance that is possible, is to develop a preprocessing step involving optimal adaptive estimation of the local clutter background. This involves segmenting the image into regions, which correspond to different background/clutter statistical models. Statistics of real data will be studied and used in new, state-of-the-art hierarchical segmentation algorithms based on Markov Random Field, polynomial and autoregressive models for vector-valued random processes. The major algorithmic challenges here are in estimating the best possible background/clutter models and in accurately estimating the boundaries between different model regions. At region boundaries, it is very important to set up a covariance involving the statistics from the models on both sides; otherwise, the matched filter's target detection performance would be severely degraded. This step is of great practical importance because tanks, missile launchers and other critical targets are often concealed at such region boundaries, e.g., at tree lines.

The main current focus of our work in progress is directed to estimating our basic image statistical models (Markov Random Fields = MRF's) with new, more efficient algorithm formulations, similar in spirit to those discovered in mainstream signal processing in the last two decades. There is an important difference involved, because mainstream signal processing is mainly concerned with problems of optimum linear *prediction*, generally in one dimension, whereas Markov Random Fields require solving an optimum *interpolation* problem, which must be two-dimensional for work on images. Whereas methodologies for fast computation have been extensively studied for the one-dimensional case, that is not the situation for the more difficult two-dimensional case. However, the prediction and interpolation problems are similar enough that helpful analogies can be made. Thus, we have been able to benefit from some of the insights and progress reflected e.g. in mainstream split Levinson or Schur techniques, although the mathematical formulation needed for MRF's does end up being somewhat different than that for prediction-based signal processing.

The other current focus is directed to new stochastic-geometric models and their use for urban clutter. Involved here are explicit polynomial surfaces, line and curve boundaries, and appropriate use of local clutter measurements in the detection process through use of Bayesian methods.

2.1 Importance of Markov Random Fields

What is Innovative in This Research

Have connected MRF estimation with an optimal interpolation problem; for the first time, it is now possible to get the same fast, powerful results for interpolation that modern signal processing has achieved for similar prediction problems.

Importance of Markov Random Fields (MRF's) for ARPA Goals in Advanced Target Detection

- Powerful, advanced method to model a wide variety of spatial statistical phenomena
- Sophisticated clutter models needed in scenarios with stochastic, partially obscured, low-observable or low-SNR targets, time-critical targets
- Goal: to advance the state-of-the-art in image segmentation, especially accuracy, computational cost, adaptivity; especially useful for targets at region boundaries (tanks by treelines)

Critique: Shortcomings of Popular Current Methods to Estimate Markov Random Fields

- Simulated annealing: huge computational complexity
- Pseudolikelihood: does not use true joint likelihood function, hence does not exploit all information available from data; not optimal
- Circulant method: forces unnatural periodic grid structure on image, does not respect natural region boundaries

3 Summary Year 2 Progress

3.1 Theoretical Advances

3.1.1 Multicovariance Matched Filters

- Have defined and studied new **generalized signal-to-noise/clutter ratio**, to characterize detection performance of multicovariance matched filter for multichannel sensors

- Shows **impact of channel correlation** on detectability– can be much better or much worse than "textbook" case
- **Figure and Ground**: determined quantitatively which targets stand out against which backgrounds
- Sensitive to important statistical features such as variable target signature, channel imbalance, clutter second-order statistics, etc.

3.1.2 Markov Random Fields

Advantages of Markov Random Fields (MRF's) to Characterize Spatial Clutter in Images

- **Mathematically solid, Bayesian formalism**– not an ad hoc or purely data-driven approach to recognition
- Allows for **nonhomogeneous spatial statistics**
  - Typical of SAR images: different signal processing and statistics for range and cross-range, even when resolutions are comparable
  - Typical of many IR and visible scanning sensors– different measurement errors associated with crosstrack and along-track directions e.g. in LANDSAT
- **Intuitively Appealing**: describes influence of close spatial neighbor values on conditional probability of value at central pixel

  Also has physical interpretation in terms of Gibbs interaction potential for a lattice structure (e.g. Ising model for magnetism is a Markov Random Field model)
- Estimation can be formulated and solved **adaptively**
- We would add: estimation problem is similar to the prediction problem studied in modern signal processing; many fast, powerful algorithms can be formulated by analogy with mainstream signal processing
- Much more sophisticated than simple-minded CFAR algorithms, which assume a constant background level– allows for trends, much more variability or inhomogeneity in the data
- Reasonably low number of parameters, unlike the large number in a sample covariance that is estimated from the data with no structure or model assumed
- A focus of much active research in the community

3.1.3 Parameter Estimation For MRF Model Parameters

- **Highly efficient, robust algorithms for spatial statistics:** Algorithm development in progress, to extend popular signal-processing estimation techniques (lattice filters) to estimating two-dimensional image statistics (Markov Random Fields)
  - Introduced Chebyshev transform: similar to Discrete Cosine Transform, Karhunen-Loeve expansion, but better orthogonal decomposition of autocorrelation
  - New inversion technique for Toeplitz-plus-Hankel matrices, using fast 3-term recurrence to orthogonalize a special set of basis functions
  - Fast covariance inversion also applicable to adaptive SAR processing

3.2 Initial Progress: Bayesian Models for Urban Clutter

Developed general approach to testing for target versus clutter image data within a target-test-region conditioned on the clutter estimated in the surrounding clutter-measurement-region. This powerful test is premised on the observation that knowledge of spatially-local image data statistics plays an important role in making a decision about whether the data in a specific target-test-region that is compatible or is incompatible with the data measured in the surrounding clutter region. In particular, under the hypothesis that clutter only is present in a target-test-region, the image data must be continuous in intensity across the target-test-region/clutter-measurement-region boundary and statistically consistent on both sides. Therefore, accurate and computationally efficient modeling of clutter within the clutter-measurement-region leads to a more powerful test than the mean gray-level comparison performed by conventional CFAR's.

3.3 Experimental Performance Evaluation

- Have characterized analytically what constitutes optimistic and pessimistic scenarios for multichannel target detection
- Data sets utilized
  - Multispectral aerial photographic imagery: terrain such as Newport, RI, taken from U2
  - LANDSAT and TIMS (6-band, thermal IR) imagery

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